# Fuzzy Systems Neural Networks and Makov Switching AR Model for Prediction of Exchange Rates

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***Abstract***

Many international agents (e.g. money managers, investment banks, investors, funds makers and others) are very concerned about predicted values of exchange rates because it often moves dustically and generally affects the profits. This paper forecasted the daily Bangladeshi and Canadian exchange rates for the period of October 1996 to January 2013. With attention paid to recently developed econometric noises, the widely-used forecasting model the fuzzy extension of artificial neural network is considered and compared results with the Markov switching autoregressive forecasting model. Root mean square error and correlation coefficient are used as an evaluation measures. It has been found that the fuzzy extension of the artificial neural network model is a superior predictor compared to the other selected predictor for the Bangladeshi series and the reverse observed for the Canadian series. It is believed that the findings of this paper will be helpful for multinational organizations wanting to make wise policy about these two country's exchange rates.

***Keywords***

*Exchange Rate Dynamics; Time Series Prediction; Non-Linearities; Econometric Noises; Aritificial Intelligence; Markov Switching Model*

## Introduction

Rate at which one currency is converted into another currency (e.g. for the purpose of travel, for engaging in speculation or trading in the foreign exchange market and others) is known as exchange rate. There are a variety of factors (e.g interest rates, inflation, the state of politics and the economy in each country and others) generally influencing the exchange rates. For this reason, it often moves significantly and commonly affects the profits of Multinational Companies (MNCs) engaged in various international business activities. Thus, understanding and forecasting exchange rate tendencies are very important to make a wide range of decisions for MNCs (investors, money managers, investments banks, hedge funds and others).

A large number of research [(Kodogiannis and Lolis, 2002), (Kuan and Liu, 1995), (Lisi and Schiavo, 1999), (Zhang and Hu, 1998), (Ismail and Isa, 2006), (Ping-Feng et al, 2006), (Tae and Steurer, 1995), (Dueker and Neely, 2007), (Hung, 2007), (Engel and Hamilton, 1990)] have been published in literature to find an optimal (or nearly optimal) prediction model for the exchange rate series. Many researches [(Kodogiannis and Lolis, 2002), (Kuan and Liu, 1995), (Lisi and Schiavo, 1999), (Zhang and Hu, 1998), (Ismail and Isa, 2006), (Ping-Feng et al, 2006), (Tae and Steurer, 1995), (Jang, 1993), (Banik et al, 2009)] have shown that the behavior of this series cannot be modelled solely by the linear time series models (e.g. regression model, time series model proposed by (Box and Jenkins, 1970) and others) because exchange rates are quite complex, non-linear, and unconstant in nature. Thus, developing a model for forecasting needs an iterative process of knowledge discovery, system improvement through data mining as well as trial and error experimentation.

To address this problem, in recent years [(Kodogiannis and Lolis, 2002), (Kuan and Liu, 1995), (Lisi and Schiavo, 1999), (Zhang and Hu, 1998), (Ismail and Isa, 2006), (Ping-Feng et al, 2006), (Tae and Steurer, 1995), (Dueker and Neely, 2007), (Hung, 2007), (Engel and Hamilton, 1990)], an increasing interest of scholars have been witnessed modeling data as nonlinear models including: artificial intelligence (AI) model, fuzzy logic model, genetic algorithm model, hybridization of ANN and fuzzy system model, Markov switching (MS) model, conditional heteroskedastic models, rough set theory, ant colony method, bee colony method and others.

In literature, we have noticed that there is a growing interest in using AI models [(Kodogiannis and Lolis,

2002), (Kuan and Liu, 1995), (Lisi and Schiavo, 1999), (Zhang and Hu, 1998), (Ping-Feng et al, 2006), (Tae and Steurer, 1995), (Jang, 1993), (Banik et al, 2009) and many others] to forecast exchange rate series. The reason for this rising popularity is that these models pay particular attention to non-linearities and learning processes both of which can help companies to improve their predictions for complex variables. The most common AI model (e.g. fuzzy extension of aritificial neural network (ANN)) is particularly useful for future predictions for variables, which is subject to non-linearities. Although ANN based models are found to perform better compared to conventional statistical models, the main drawback of ANN models is that their prediction capabilities deteriorate over a short period of time especially when data are very much chaotic. It has been proposed by many authors [(Kodogiannis and Lolis, 2002), (Lisi and Schiavo, 1999), (Banik et al, 2009)] to overcome this drawback and develop a reliable prediction of time series data. We have chosen the fuzzy extension of AI model and compared our results with the widely used MS model [(Ismail and Isa, 2006), (Dueker and Neely, 2007), (Hung, 2007), (Hamilton, 1989)] to predict Bangladeshi (BER), and Canadian (CER) exchange rates series in order to see whether selected models can help companies to raise predictive power. By analyzing applied models validity and precision, our plan is to develop the model which can best predict the selected series.

A lot of works have been done in literature to predict exchange rate based on statistical and AI models. For example, (Ismail and Isa, 2006) used the MS model to predict the exchange rates for three ASEAN countries (Malaysia, Singapore and Thailand), and compared their results with the autoregressive (AR) model of order p. Results show that the MS model predicted well than the AR model. (Kodogiannis and Lolis, 2002) examined the forecasting ability of daily exchange rate values of the US Dollar vs. British Pound using the neuro-fuzzy systems and compared with various networks. They found that the neuro-fuzzy systems outperform the other networks. (Kuan and Liu, 1995) have investigated the forecasting ability of feed-forward and recurrent neural networks based Japanese yen, British pound, Canadian dollar, Deutsche mark etc. Their results show that the selected network models have significant market timing ability relative to the random walk model. (Zhang and Hu, 1998) have successfully used neural network for predicting British pound/US dollar exchange rates. Their results show that the neural network outperforms the linear model. (Tae and Steurer,1995) compared the Deutsche mark monthly and weekly exchange rates using the neural networks and the statistical model, leading to the result that the neural net outperforms the statistical model. (Lisi and Schiavo, 1999) investigated the monthly exchange rates of the four major European currencies from 1973 to 1995 using the neural network and compared with the random walk model, and got the results that neural network turn out to be statistically better than the random walk model.

The aim of this paper is to investigate whether our selected models can serve useful tools to describe the behavior of BER and CER series more efficiently. To our knowledge, with caring econometric noises forecasting selected BER and CER daily series under the powerful nonlinear models are yet considered in the existing literature which have considered this research in this paper. Thus it is believed that findings of the paper will be useful for those who are interested to make wise policies about the complex variables BER and CER. The paper is outlined as follows: section 2 describes about the data set and numerical properties. Considered forecasting models are reviewed in section 3. Section 4 contains experimental designs and findings. Concluding remarks and some future research plans are given in section 5.

## Data, Forecasting Model, Numerical Properties and Econometric Noises

We considered the daily BER and CER series over the period of October 1996 to January 2013 for a total of 5934 observations. BER and CER are the local currency against the US dollar, collected from the site of http://www.oanda.com/currency/historical-rates/. The training and testing data sets and for understanding of changes, series are depicted in Fig. 1 (BER series) and Fig. 2 (CER series) respectively. It is very clear that there is an increasing trend w.r.t to time for BER and a decreasing trend for CER series. There have some reasons why these sorts of trends exist. See above website for details. It is also observed from these plots that the behaviors of series are non-linear, meaning that series can appear unconstant with moves that look chaotic. Some sort of non-linearity can also present in the selected series.

### Numerical Properties

To understand behaviors of daily BER and CER series,

summary statistics are reported in Table 1. It is noticed that exchange rate patterns for BER and CER do not follow the normal distribution. Since our series are time series, so we have selected most commonly used time series model, namely, the autoregressive (AR) model of order p. The model is defined for BER and CER series are as follows:

$$BER_t = \alpha+\beta t+\rho_i\, BER_{t-i} + e_t, \quad t = 1,2,3,\ldots,n \qquad (2.1)$$

$$CER_t = \alpha+\beta t +\rho_i\, CER_{t-i}+e_t, \quad t = 1,2,3,\ldots,n \qquad (2.2)$$

where $\alpha$ is an intercept, $\beta$ is the deterministic trend, t is the time variable, $\rho_i$ are the lag orders of the AR(p) model and $e_t \sim N(0,\sigma^2)$. The appropriate lags of the series are selected by the Bayesian Information Criterion (BIC). It is started by calculating BIC (e.g. Akaike Information Criterion(AIC), Sibata Information Criterion(SIC) and others can also be used) to find the number of lags used in AR process for BER and CER. To calculate BIC, we followed the following steps:

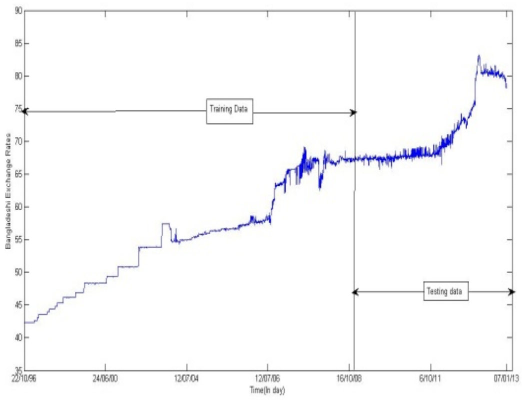


FIG. 1 TIME PLOTS OF BER SERIES

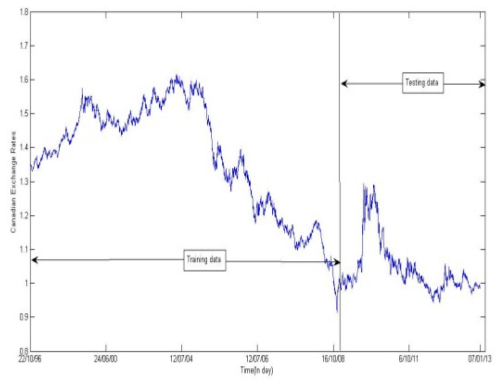


FIG. 2 TIME PLOTS OF CER SERIES

Various AR models have been utilized by increasing the order of AR, p. The formula is defined as

$$-2L+X_t \ln(n)$$

where n is the sample size, L is the maximized log-likelihood of the model and $X_t$ includes an intercept and lags of series. Then we have chosen the model that gives the smallest value of BIC. It is noted that the lag length of series is selected based on a maximum lag of 8. It has been found that the number of lags to be used is 1 and 4 for the considered series. Based on this information, AR(1) for BER series and AR(4) model is considered for AR(4) for CER series. See Table 2 for proposed AR(p) model.

TABLE 1 DESCRIPTIVE STATISTICS OF BER AND CER FOR OCTOBER 1996 TO JANUARY 2013

| Series | Statistical measures | | | | | | |
|---|---|---|---|---|---|---|---|
| | n | Min Rate | Max rate | Mean Rate | SD Rate | Skew | Kur |
| BER | 5934 | 42.35 | 83.15 | 60.38 | 10.09 | 0.077 | 2.216 |
| CER | 5934 | 0.914 | 1.615 | 1.269 | 0.208 | 0.008 | 1.516 |

TABLE 2 STATIONARITY TEST RESULTS

| Rates | Proposed AR(p) Model | ADF(p) statistic | p-value (critical value) for ADF test | PP(L) statistic | p-value (critical value) for PP test |
|---|---|---|---|---|---|
| BER | AR(1) | -0.988(1) | 0.141 (-3.414) | -1.13(8) | 0.768 (-3.414) |
| CER | AR(4) | -1.233(4) | 0.759 ( -3.414) | -1.29(5) | 0.2627 (-3.414) |

Note: 'p' and 'L' indicate lag order to remove serial correlation.

Decision rule: If p-value<level of significance ($\alpha$), then accept null hypothesis

## Econometric Noises

Numerous studies (e.g. [(Nelson and Plosser, 1982), (Mitchell, 1999), (Banik,1999), (Banik and Silvapulle, 1999), (Said and Dickey, 1984), (Phillips and Perron, 1988)] and many others) have suggested that most time series are non-stationary (contains a unit root). Therefore, assumption of stationarity is unrealistic. Thus, prior to model specifications and estimations, stationary property of data series is routinely tested (see Banik,1999, details), otherwise the study can yield unrealistic results. That's why appropriate forecasting model should be selected for BER and CER series, and at first, stationarity property of the series was tested.

Many stationarity tests are available in time series literature (details, see [(Green, 2008), (Banik,1999)] and others). To test the stationarity behavior of our considered models (2.1)-(2.2), commonly applied unit root tests, namely the ADF test proposed by (Said and Dickey, 1984) and the PP test proposed by (Phillip and Perron, 1988)] are used (for test procedures, see (Banik,1999)). Note that under the null hypothesis of ADF and PP tests, series is assumed non-stationary and under the alternative hypothesis, series is

stationary. Results (Table 2) show that BER and CER series are non-stationary (because p-value>$\alpha$, $\alpha$=0.05). Then we have taken the first difference of the series to remove non-stationarity and applied again ADF test and PP test. Our results show that in first differences considered BER and CER series are stationary (these results are not reported for spaces but are available on request). The effect of these tests will be shown when our forecasting model was used, in first differences.

Considered statistical tests ((Table 2) results show that BER and CER series are non-stationary and non-linear [Figs 1-2], respectively. To remove non-stationarity from selected series, we have used series in first differences. Thus, based on above findings, nonlinear forecasting models have been selected to forecast BER and CER which have also ability to capture chaotic behavior. A brief description of the considered forecasting models is given below.

## Forecasting Models

### *Fuzzy Extension of Neural Network Model*

Based on the theory of fuzzy set and logic, this architecture (also known as adaptive neural fuzzy inference system (ANFIS)) proposed by (Jang, 1993) is a combination of neural network (NN) system and fuzzy inference system (FIS) in such a way that the NN learning algorithm is used to determine the parameters of FIS. NN is non-linear statistical data modeling tool, which can capture and model any intput-output relationships. In addition, FIS, the process of formulating the mapping from a given input to an output using fuzzy logic, involves: membership functions (mfs), fuzzy logic operators and if-then-rules.

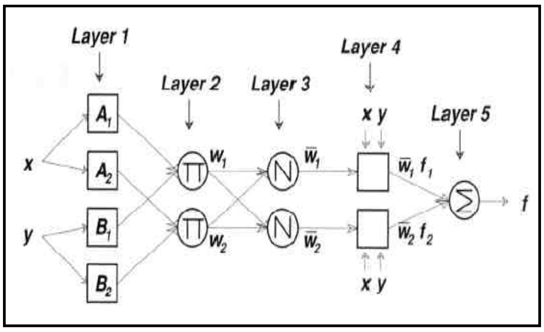


FIG. 3 AN ANFIS ARCHITECTURE WITH A 2-INPUT, 2-RULE FIRST-ORDER SUGENO MODEL

A typical ANFIS architecture is given in Fig. 3 showing that ANFIS has 1 input layer, 3 hidden layers (that represents mfs and fuzzy rules) and 1 output layer. It uses Sugeno-fuzzy inference model to be thelearning algorithm. In Fig. 3, the circular nodes represent fixed nodes whereas the square nodes are nodes that have parameters to be learnt. Each layer in this figure is associated with a particular step in FIS. The following concepts concerns the process, where the input vector is fed through the ANFIS network layer by layer:

Layer 1: *Fuzzy layer (generates mfs grades):* Input x to $A_1$ and $A_2$ and input y to $B_1$ and $B_2$ respectively, where $A_1$, $A_2$, $B_1$ and $B_2$ [fuzzy sets] are the lingiustic expressions which are used to distinguish the mfs represented by the premise parameters (PP). The relationship between the input-output mfs: $O^1_{A_i} = \mu_{A_i}(x)$ ; $O^1_{B_i} = \mu_{B_i}(y)$ , i=1,2, where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ denote mfs. Any continuous and piecewise differentiable functions such as generalised bell-shape mfs, gaussain-shaped mfs, triangular-shaped mfs, trapezoidal-shaped mfs can be used in this layer.

Layer 2: *Production layer (generate the firing strenghts):* It is marked as $\Pi$ and output is defined as $O^2_i$ = $W_i$ = $\mu_{A_i}(x) \times \mu_{B_i}(y)$ , where $W_i$, i=1,2 are weight functions of the next layer. Here the t-norm "product" is used as fuzzy operator.

Layer 3: *Normalized layer (normalize the firing strength):* It is marked as N and used to normalize $W_i$ (i.e. it calculates the ratio of firing strength of the rules with the total firing strenghts). It is defined as: $O^3_i$ = $\overline{W}_i = W_i / \sum_{i=1}^{2} W_i$, $i = 1, 2$ .

Layer 4: *Defuzzy layer (calculates output rules):* Here an adaptive node $\overline{W}_i$ is outputs and {$p_i$,$q_i$, $r_i$} is the parameter sets [known as consequent parameters (CP)] in this layer. The relationship between input and output is: $O^4_i = \overline{W}_i f_i = \overline{W}_i (p_i x + q_i y + r_i)$ , i=1,2.

Layer 5: *Total output layer (sum all inputs from the layer 4):* Its node is marked as $\Sigma$, computes the overall output. It can be expressed as: $O^5_i$ =Output =

$$\sum_{i=1}^{2} \overline{W}_i f_i = \overline{W}_i (p_i x + q_i y + r_i)$$

Next step is to examine how the ANFIS learns PP and CP for the mfs and the rules. From Fig. 3, it is clear that the final layer output can be expressed as a linear combination of the CP. In symbols, f = ($\overline{W}_1$ x)$p_1$+($\overline{W}_1$ y)$q_1$+( $\overline{W}_1$ )$r_1$+( $\overline{W}_2$ x)$p_2$+( $\overline{W}_2$ y)$q_2$+( $\overline{W}_2$ )$r_2$. Thus, we have a set of total ANFIS parameters S, which is calculated as S = S1$\cup$S2, where S1 = set of PP(non-

linear) and S2 = set of CP(linear). The learning algorithm of ANFIS is a hybrid algorithm, which combines the gradient descent (GD) method and the least square estimation (LSE) for an effective search of PP and CP, which means that ANFIS uses a two pass of learning algorithm to reduce the error: (i) Forward pass and (ii) backward pass. The hidden layer is computed by the GD method of the feedback structure and the final output is estimated by the LSE.

The output equation from the layer 5 can be rearranged as more usable form: Y = XW, where X=[$\overline{W}_1 x$ $\overline{W}_1 y$ , $\overline{W}_1$ , $\overline{W}_2 x$ , $\overline{W}_2 y$ , $\overline{W}_2$ ] and W = [$p_1$, $q_1$, $r_1$, $p_2$, $q_2$, $r_2$]$^T$. When the input-output training pattern exists, the vector W can be solved using the ANFIS learning algorithm .

### *The MS Model*

Changes in regime happen quite suddenly in real world. For example, exchange rate appears to follow long swings, which means that rate drifts upward for a considerable period of time and then switches to a long period with a downward drift. To model this dramatic change, a more practical model is the Markov switching autoregressive (MS_AR) model, developed by (Hamilton, 1989). To understand the model clearly, consider the BER and CER at time t and $S_t$ is an unobservable discrete state variable that takes values of 1 (appreciation period- an increase in the value of domestic currency relative to foreign currency) or 2 (depreciation period-a decrease in the value of domestic currency relative to foreign currency).

The MS_AR model with two possible states is defined as follows:

$$BER_t = \alpha_{S_t} X_t + e_t, \quad S_t \in \{1,2\}, \ t = 1,2,\ldots,n$$

$$CER_t = \alpha_{S_t} X_t + e_t, \quad S_t \in \{1,2\}, \ t = 1,2,\ldots,n$$

where $X_t$ includes an intercept (denoted by $\mu_i$, i =1,2) and lags of the dependent variable $BER_t$ and CER, $\alpha_{S_t}$ are the corresponding parameters and $e_t \sim N(0, \sigma^2_{S_t})$ a random variable with a state dependent variance $\sigma^2_{S_t}$ . The changes in states are rules by transition probabilities which are governed by a first order Markov process as follows:

$$P(S_t = 1 \mid S_{t-1} = 1) = p_{11}$$

$$P(S_t = 1 \mid S_{t-1} = 2) = p_{12}$$

$$P(S_t = 2 \mid S_{t-1} = 1) = p_{21}$$

$$P(S_t = 2 \mid S_{t-1} = 2) = p_{22}$$

with $p_{11} + p_{21}=1$ and $p_{12} + p_{22}=1$, where $p_{ij}$(i=1,2 and j=1,2) are the transition probabilities for switching from one state to other state. As $S_t$ is unobserved, the parameter vector (say) $\theta$ =($\alpha_{S_t}$ ,$\sigma_1$, $\sigma_2$, $p_{11}$, $p_{12}$, $p_{21}$, $p_{22}$) is estimated by the maximum likelihood method using the EM algorithm developed by (Hamilton, 1989). Here fitted series will be calculated by the probability of $S_t$=1or 2 based on the observed series.

## Experimentation, Results and Discussion

### *Experimentation*

The first 70% observations for daily BER and CER series are used as the training period and the rest as the testing period [see Figs 1-2]. All computational works were carried out using the programming code of MATLAB.

### *Results*

#### *(1) The ANFIS Model*

A trial and error approach is used to design the topology of ANFIS. The best performance is obtained by a network consisting of: 4 inputs with 2 mfs (type Gaussian-shaped) with each input, 8 if-then fuzzy rules were learned, total parameters (44)=premise parameters(12) + consequent parameters (32), where premise parameters are calculated by number of inputs×number of mfs×number of parameters of Gaussian distribution and consequent parameters is calculated by number of mfs×number of parameters of Gaussian distribution × number of fuzzy rules.

The training data has been used with the MATLAB command Genfis1 in order to create a FIS. Thus, the following ANFIS forecasting models was selected to forecast BER and CER values:

$$P_{5th\,day\_BER} = f(day1\_BER, day2\_BER, day3\_BER, day4\_BER)$$

$$P_{5th\,day\_CER} = f(day1\_CER, day2\_CER, day3\_CER, day4\_CER)$$

#### *(2) The MS_AR Model*

It is started by calculating BIC to find the number of lags used in AR process for BER and CER. It was found that the number of lags to be used is 1 and 4 for BER and CER. Based on this information, a MS with AR(1) for BER series and a MS with AR(4) model are considered for AR(4) and CER series and all parameters have been estimated using the maximum likelihood method.

TABLE 3A PARAMETERS ESTIMATES FOR THE MS_AR(1) MODEL FOR STATE 1 AND BER SERIES

| | $\mu_1$ | $\sigma_1$ | $\alpha_{11}$ |
|---|---|---|---|
| **Parameters estimates** | 0.0020<br>(0.0005) | 0.0324<br>(0.0030) | -0.1213<br>(0.0124) |

Note: Standard errors are in parenthesis

TABLE 3B PARAMETERS ESTIMATES FOR THE MS_AR(1) MODEL FOR STATE 2 AND BER SERIES

| | $\mu_2$ | $\sigma_2$ | $\alpha_{21}$ |
|---|---|---|---|
| **Parameters estimates** | 0.0041<br>(0.013) | 0.0213<br>(0.0012) | 0.2012<br>(0.0345) |

Note: Standard errors are in parenthesis

TABLE 3C TRANSITION PROBABILITY MATRIX

$$\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} 0.46 & 0.35 \\ 0.54 & 0.65 \end{bmatrix}$$

TABLE 4A PARAMETERS ESTIMATES FOR THE MS_AR(4) MODEL FOR STATE 1 AND FOR CER SERIES

| | $\mu_1$ | $\sigma_1$ | $\alpha_{11}$ | $\alpha_{12}$ | $\alpha_{13}$ | $\alpha_{14}$ |
|---|---|---|---|---|---|---|
| **Parameters estimates** | 0.0002<br>(0.0001) | 0.0045<br>(0.0003) | -0.0065<br>(0.0245) | -0.3429<br>(0.0134) | -0.5468<br>(0.0312) | -0.1302<br>(0.0528) |

Note: Standard errors are in parenthesis

TABLE 4B PARAMETERS ESTIMATES FOR THE MS_AR(4) MODEL FOR STATE 1 AND FOR CER SERIES

| | $\mu_2$ | $\sigma_2$ | $\alpha_{21}$ | $\alpha_{22}$ | $\alpha_{23}$ | $\alpha_{24}$ |
|---|---|---|---|---|---|---|
| **Parameters estimates** | 0.0009<br>(0.002) | 0.4138<br>(0.0112) | 0.3000<br>(0.0720) | -0.0400<br>(0.1260) | 0.0057<br>(0.0287) | 0.0078<br>(0.0487) |

Note: Standard errors are in parenthesis

TABLE 4C TRANSITION PROBABILITY MATRIX

$$\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} 0.78 & 0.29 \\ 022 & 0.71 \end{bmatrix}$$

Results are reported in Tables 3A-3C for BER series and Tables 4A-4C for CER series. These parameters estimates are used to forecast daily BER and CER.

### *Discussion of Results*

Forecasting performances are evaluated against two widely used statistical metrics, namely, root mean square error (RMSE) and correlation coefficient (CORR). The formulas are defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Actual}_i - \text{Predicted}_i)^2}$$

$$\text{CORR} = \frac{\text{Cov}(\text{Actual} - \text{Predicted})}{\sigma_{\text{Actual}}\sigma_{\text{Predicted}}}$$

Smaller values RMSE indicate higher day accuracy in forecasting. While higher CORR indicates better prediction.

To evaluate predicted and actual exchange rates, prediction performance is measured in terms of RMSE and CORR over the training and testing data. Tables 5 and 6 summarize the performances of considered forecasting models for BER series in Tables 7 and 8 for CER series. In terms of measures of RMSE and CORR (see Table 5), our training results show that the ANFIS forecasting model outperforms (noted smallest RMSE value and highest CORR value) the MS_AR(1) forecasting model. The highest CORR values (i.e. good match between actual and predicted BER) again indicated that the ANFIS forecasting model outperforms the MS_AR(1) model. For example, the accuracy of prediction for the ANFIS forecasting model is 95.46% and for the MS_AR(1) forecasting model 92.65% respectively. After the considered models have been built using the training data, BER series is forecasted over the testing data and performance measures are reported in Table 6. The testing results (see Table 6) show that BER prediction capability of ANFIS forecasting model is higher again (found the lowest RMSE value and highest CORR values) compared to the that of MS_AR(1) model.

TABLE 5 PERFORMANCE MEASURES FOR TRAINING DATA AND FOR BER SERIES

| Performances metrics | ANFIS | MS_AR(4) |
|---|---|---|
| RMSE | 1.2359 | 4.2180 |
| CORR | 0.9546 | 0.9265 |

TABLE 6 PERFORMANCE MEASURES FOR TESTING DATA AND FOR BER SERIES

| Performances metrics | ANFIS | MS_AR(4) |
|---|---|---|
| RMSE | 1.1045 | 3.8796 |
| CORR | 0.9672 | 0.9349 |

TABLE 7 PERFORMANCE MEASURES FOR TRAINING DATA AND FOR CER SERIES

| Performances metrics | ANFIS | MS_AR(4) |
|---|---|---|
| RMSE | 5.0301 | 2.5298 |
| CORR | 0.8994 | 0.9336 |

TABLE 8 PERFORMANCE MEASURES FOR TESTING DATA AND FOR CER SERIES

| Performances metrics | ANFIS | MS_AR(4) |
|---|---|---|
| RMSE | 4.6780 | 2.0970 |
| CORR | 0.9999 | 0.95365 |

In order to find out how well our considered models fitted to the actual CER data, Table 7 and Table 8 have been added. For training data, it shows clearly that the MS_AR(4) forecasting model outperforms (noted smallest RMSE value and highest CORR value) the ANFIS forecasting model. The testing results (see Table 8) show that CER prediction capability of MS_AR(4) forecasting model is higher again (found

the lowest RMSE value and highest CORR value) compared to that of the ANFIS model, meaning more significant differences in the ANFIS model observed between the actual CER and that predicted by the ANFIS than in the MS_AR(4) forecasting model.

According to our findings, the ANFIS forecasting model appears to be more suitable for BER series modeling and the MS_AR forecasting model for CER series.

## Conclusion

In this paper, the popular forecasting models (i.e. the ANFIS model and the MS_AR model) have been considered to predict daily BER and CER series for the period October 1998 to January 2013. The forecasting performances of selected models were measured by widely used measures RMSE and CORR. Our findings suggested that the ANFIS forecasting model can forecast the daily BER series closely as compare to the MS_AR forecasting model. The MS_AR forecasting model appeared to be more suitable for CER series modeling. It was believed that our findings will be useful for researchers in making wise decisions about BER and CER series.

Our next step is to improve forecasting results using recently widely used the rough set forecasting model, where stock data, market demand and supply data could be regarded as input variables to predict more accurately daily BER and CER. This is focus of future research.

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